INCORPORATING EDGE INFORMATION INTO BEST MERGE REGION-GROWING SEGMENTATION

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1. INTRODUCTION

Described and discussed in [1] Tilton, *et al* is a best merge region-growing segmentation approach that integrates nonadjacent region object aggregation with the neighboring region merging process usually employed in region growing segmentation approaches. This approach has been named HSeg, because it provides a hierarchical set of image segmentation results. We have noted that in some of the more detailed levels of the HSeg segmentation hierarchy, large and apparently homogeneous areas are sometimes separated into more than one region with region boundaries that do not correspond to any apparent object boundary. It is apparent that HSeg is responding to gradual changes in region features that are not important for most image analysis applications. Realizing that previous versions of HSeg consider only global region feature information in the region growing decision process, we have devised an augmentation of HSeg that incorporates local edge information into the region growing process. We expect that this should make HSeg less sensitive to gradual changes in regions features, and generally improve the performance of HSeg. We use edge information generated by the Frei-Chen edge operator [2] in our augmentation of HSeg. The Frei-Chen edge operator applies a combination of nine convolution masks to generate a normalized edge image that is sensitive to lines and/or edges in the horizontal, vertical and diagonal directions.

The next two sections of this paper summarize the previous HSeg image segmentation approach (version 1.59, similar to the version described in [1]) and the Frei-Chen edge operator. We then describe three alternate approaches (versions 1.61, 1.71, and 1.80) for incorporating the Frei-Chen edge information into HSeg. We follow this with an evaluation of the effectiveness of these approaches as compared to version 1.59. We conclude with a discussion of the results and considerations for future work.

2. THE HSEG SEGMENTATION APPROACH

The HSeg image segmentation approach is based on hierarchical step-wise optimization (HSWO) as describe in [3]. HSWO is an iterative form of region growing, in which the iterations consist of finding the most optimal or best segmentation with one less region than the current segmentation. HSWO is performed by finding a threshold value, T_{merge}, equal to the value of a dissimilarity criterion of the most similar pair of spatially adjacent regions, and then merging all pairs of regions that have dissimilarity equal to T_{merge}. HSeg adds to HSWO a step following each step of adjacent region merges in which all pairs of spatially non-adjacent regions are merged that have dissimilarity <= $S_w T_{merge}$, where 0.0 <= S_w <= 1.0 is a factor that sets the priority between spatially adjacent and non-adjacent region merges. Note that when S_w = 0.0, HSeg reduces to HSWO. HSeg provides choices among several dissimilarity criteria, including one based on minimizing the increase of mean squared error between the region mean image and the original image data, and one based on the Spectral Angle Mapper (SAM) criterion [4]. All of these dissimilarity criterion depend on global region features such as region size (number of pixels), sum of pixel values in each spectral band and sum of the square pixel values in each spectral band. See [1] for a more complete description of HSeg and the dissimilarity criterion utilized by HSeg.

3. FREI-CHEN EDGE OPERATOR

The Frei-Chen edge operator was first described in [2]. More recent updates of the Frei-Chen edge operator have resulted in a revision of the weighting factors for the Frei-Chen masks (see [5]). Following [5], the Frei-Chen edge operator consists of the nine following unique 3x3 convolution masks:

$$G_1 = \frac{1}{2\sqrt{2}}\begin{bmatrix} 1 & \sqrt{2} & 1 \\ 0 & 0 & 0 \\ -1 & -\sqrt{2} & -1 \end{bmatrix} \quad G_2 = \frac{1}{2\sqrt{2}}\begin{bmatrix} 1 & 0 & -1 \\ \sqrt{2} & 0 & -\sqrt{2} \\ 1 & 0 & -1 \end{bmatrix} \quad G_3 = \frac{1}{2\sqrt{2}}\begin{bmatrix} 0 & -1 & \sqrt{2} \\ 1 & 0 & -1 \\ -\sqrt{2} & 1 & 0 \end{bmatrix}$$

$$G_4 = \frac{1}{2\sqrt{2}}\begin{bmatrix} \sqrt{2} & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & -\sqrt{2} \end{bmatrix} \quad G_5 = \frac{1}{2}\begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \quad G_6 = \frac{1}{2}\begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & -1 \end{bmatrix}$$

$$G_7 = \frac{1}{6}\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix} \quad G_8 = \frac{1}{6}\begin{bmatrix} -2 & 1 & -2 \\ 1 & 4 & 1 \\ -2 & 1 & -2 \end{bmatrix} \quad G_9 = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

The first four masks are used for edges, the next four for lines, and the last mask is to provide a mask average for normalization. Since we are interested in image edges, we compute our edge value, E_{value}, as follows:

$$E_{value} = \sqrt{\frac{M}{S}} \;\; where \;\; M = \sum_{k=1}^{4} (G_k * I)^2 \;\; and \;\; S = \sum_{k=1}^{9} (G_k * I)^2$$

The value of E_{value} will always be in the range of 0.0 through 1.0, with a value of 1.0 representing the most abrupt possible edge (a "delta" edge). Most remotely sensed images, max(E_{value}) will be less than 0.7. For multi-band images we usually use the band maximum of the edge value at each image pixel, but we can also use the band average or band minimum on an experimental basis.

4. INCORPORATING EDGE INFORMATION INTO HSEG

In our experimentation on incorporating edge information into HSeg, we have devised three distinct approaches, which we describe below. However, each of these approaches utilizes a fast merge region growing approach, first proposed in [6], to initialize the image segmentation based on the edge value information. In our implementation of this approach, we set an edge value threshold, E_{thresh}, and merge all neighboring pixels that result in regions where $\max(E_{value}) <= E_{thresh}$.

4.1. HSeg Version 1.61

This version is a simple extension of the original version in that one region feature value, E_{max}, is added to each region, which is the maximum value of E_{value} for all pixels in the region. The weighting of this edge feature is controlled by a user settable parameter, E_w. The edge dissimilarity value, E_{dissim}, is taken to be the maximum of E_{max} for the two regions being compared. We normalize the value of E_{dissim} to range from 0.0 to 1.0, by computing $E'_{dissim} = (E_{dissim} - \min_I[E_{value}])/(\max_I[E_{value}] - \min_I[E_{value}])$, where $\min_I[E_{value}]$ is the minimum value of E_{value} over the entire image, I, and $\max_I[E_{value}]$ is the maximum value of E_{value} over the entire image. An edge factor, E_f, is then computed as follows:

$$E_f = (S_w + (1.0 - S_w)((1.0 - E_w) + E'_{dissim}E_w))/S_w$$

The effect of this equation is to set $E_f = 1.0$ for $E_w = 1$ and $E'_{dissim} = 0.0$, and $E_f = 1.0/S_w$ for $E_w = 1.0$ and $E'_{dissim} = 1.0$. The combined region dissimilarity is the computed as $C_{dissim} = R_{dissim}*E_f$, where R_{dissim} is the dissimilarity between the region pair for the original version of HSeg. Thus, an adjacent region is treated as a non-adjacent region for $E'_{dissim} = 1.0$, and treated normally as an adjacent region for $E'_{dissim} = 0.0$, with gradations in-between for $0.0 < E'_{dissim} < 1.0$.

4.2. HSeg Version 1.71

This version is a more complicated extension of the original version in that a region data structure is modified to enable the tracking of the value of E_{value} along the mutual boundary between two regions. The value of the edge dissimilarity value, E_{dissim}, is taken to be the average of E_{value} for all the mutual boundary pixels between the two regions. The value of E_f is then computed based on this value of E_{dissim} in the same way as for HSeg Version 1.61.

4.3. HSeg Version 1.80

This version is a yet more complicated extension of the original version in that a region data structure is modified to not only enable the tracking of the value of E_{value} along the mutual boundary between two regions, but also determine whether or not a region boundary pixel is adjacent to any other region. For this version, the value of the edge dissimilarity value, E_{dissim}, is taken to be the average of E_{value} for all the boundary pixels between the two regions that only have the other region as a neighboring region. The value of E_f is then computed based on this value of E_{dissim} in the same way as for HSeg Version 1.61.

5. COMPARATIVE RESULTS

We have conducted an experimental analysis to evaluate the effectiveness of the new versions compared to each other and to the previous version. Image segmentation results were evaluated by considering a region-based classification approach utilized in [1]. First, a pixelwise classification based on support vector machine (SVM) is applied to the image data. Then, the region classification is obtained by considering a plurality vote rule, i.e., by assigning each spatially connected region from the segmentation result to the most frequently occurring class within the region. We report here some results obtained on the well-known Indian Pines AVIRIS hyperspectral dataset. The results in terms of overall accuracy (OA), average accuracy (AA) and kappa index (K) are summarized in Table I. We note the new implementations give an improvement in terms of classification accuracies with respect to the original version.

TABLE I. COMPARISON OF CLASSIFICATION ACCURACIES ON THE INDIAN PINES DATASET

	OA	AA	K
SVM	79.23	80.41	76.27
1.59	87.48	89.64	85.63
1.61	88.65	91.23	87.00
1.71	90.32	92.52	88.90
1.80	89.88	92.10	88.40

6. CONCLUSIONS

In this paper we have proposed three alternate approaches for incorporating the edge information into HSeg image segmentation approach. Some preliminary results confirm the effectiveness of the new implementations as compared to the previous version of HSeg. We have also noted that large homogeneous areas are merged into one region much earlier in the region growing process with the new versions. We will continue to evaluate and compare these versions of HSeg on other data sets, noting the tradeoffs between computation time and segmentation quality. We have noted similar computation times between versions 1.59 and 1.61, but versions 1.71 1.80 generally have longer computations times, with version 1.80 being somewhat longer than version 1.71.

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